Statistical Machine Learning Techniques for Predicting Lung Cancer Prevalence

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Data Science Bootcamp Trainees

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Introduction

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Motivation: To learn the underlying factors contributing to lung cancer prevalence

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Goal: To identify key features associated with lung cancer incidence

Data overview: Lung Cancer in Virginia (2014-2018)

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Table: General overview of study features, with the underlying population being individuals aged 18 and over

Group	**Features**	**Source**
Demographics	% Male, % Female, % Black, % White, % Hispanic, % Age $\geq$65	US Census ACS
Behavioral	Prevalence of Smoking, Binge Drinking, and Obesity	CDC PLACES
Socioeconomic	% Below Poverty, Social Deprivation Index (SDI)	US Census, Graham Center
Environmental	PM2.5 Air Quality ($\mu g/m^3$)	EPA Downscaler

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Unobserved or missing values are removed, as there is no clear rationale for imputation

Statistical machine learning techniques

Model formulation: Let Y_i denote the number of lung cancer cases in a population of size N_i

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We model Y_i using Poisson distribution given by

$$P(Y_i = y_i) = \frac{(N_i\lambda_i)^{y_i} e^{-N_i\lambda_i}}{y_i!}, \ i = 1, 2, \cdots, n$$

Poisson generalized linear model: We model the incidence rate λ_i as $\lambda_i = \exp(\mathbf{x}_i^\top \boldsymbol{\beta})$

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Using the data $y_1, y_2, \ldots, y_n$, the objective function with elastic net regularization can be given by

$$\mathcal{L}(\boldsymbol{\beta}) = -\sum_{i=1}^{n} \left[y_i \log N_i + y_i \mathbf{x}_i^\top \boldsymbol{\beta} - N_i e^{\mathbf{x}_i^\top \boldsymbol{\beta}} - \log(y_i!) \right] + \alpha \left[\gamma \|\boldsymbol{\beta}\|_1 + \frac{1-\gamma}{2} \|\boldsymbol{\beta}\|_2^2 \right], \quad \alpha \geq 0,\ \gamma \geq 0$$

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We use this regularization approach to select features that are associated with the lung cancer incidence rate

XGBoost with Poisson Loss Function: We model the rate λ_i using tree at t-th iteration as $\log(\lambda_i) = f(\mathbf{x}_i, \eta_t)$, which is parameterized by η_t

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We use this approach to assess the importance of the selected variables in lung cancer incidence

Results of the study

Data splitting: Training data (70%) and testing data (30%)

Poisson generalized linear model

Hyperparameter selection:
Five-fold cross-validation on
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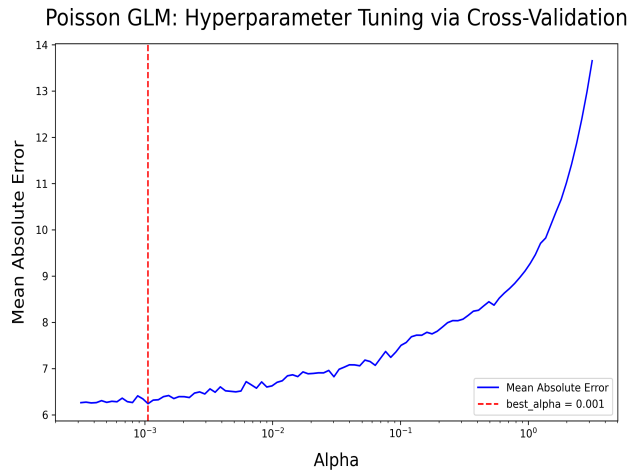
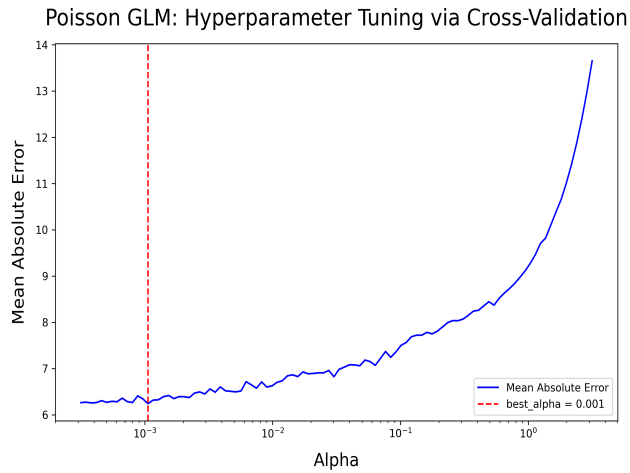


Poisson generalized linear model



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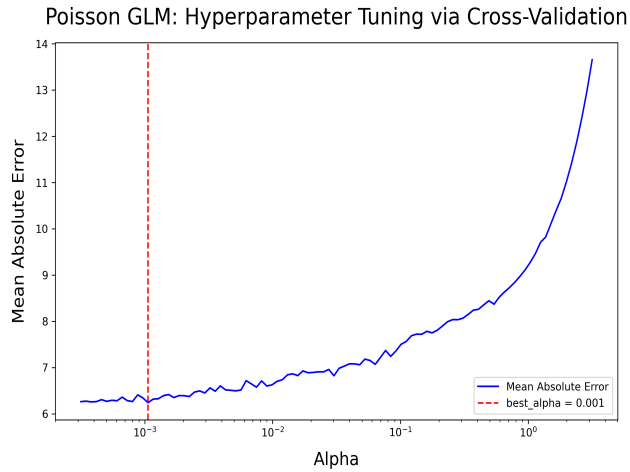

Table 1: Selected Features Using Elastic Net Regularization

Features	Parameter estimates
Pct_BelowPoverty_18andOver	-1.339
Pct_Population_Male_65andOver	2.797
Pct_Population_Female_65andOver	2.743
Pct_Black_Female_65andOver	2.487
Pct_White_65andOver	0.136
Pct_White_Male_65andOver	-0.484
Pct_Hisp_65andOver	-0.885
Pct_Hisp_Female_65andOver	-1.819
BINGE_CrudePrev	-0.017
CSMOKING_CrudePrev	0.125
OBESITY_CrudePrev	0.039
Median_Household_Income	-0.087
ZCTA_pm2_5	-0.069
sdi_score	0.034
Pct_White_Male_Between18and65	1.086
Pct_White_Female_Between18and65	1.296
Pct_Black_Female_Between18and65	1.434
Pct_Hisp_Male_Between18and65	-0.328
Pct_Hisp_Female_Between18and65	-1.263

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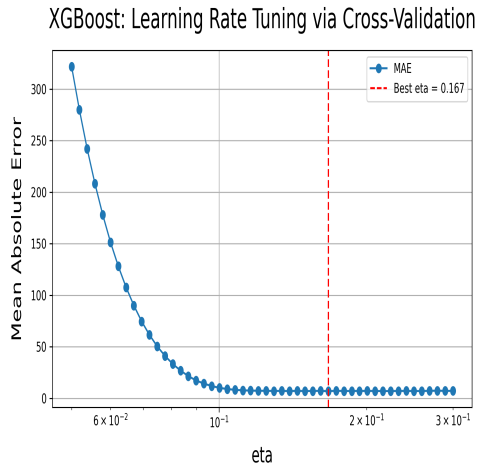

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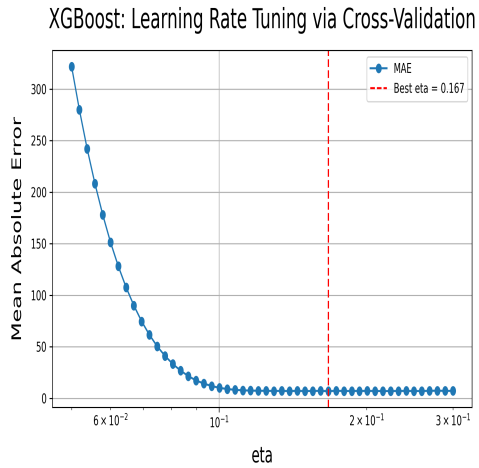
Gain index: Feature with high gain improves the model performance



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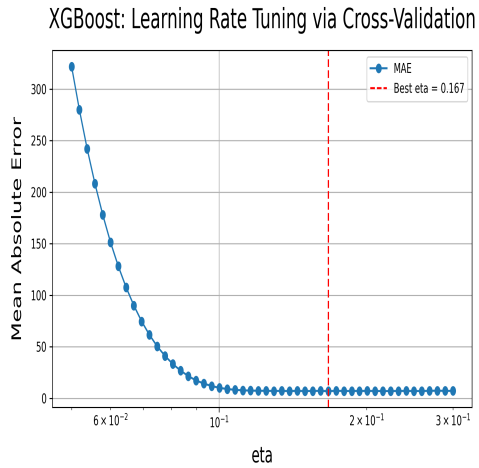
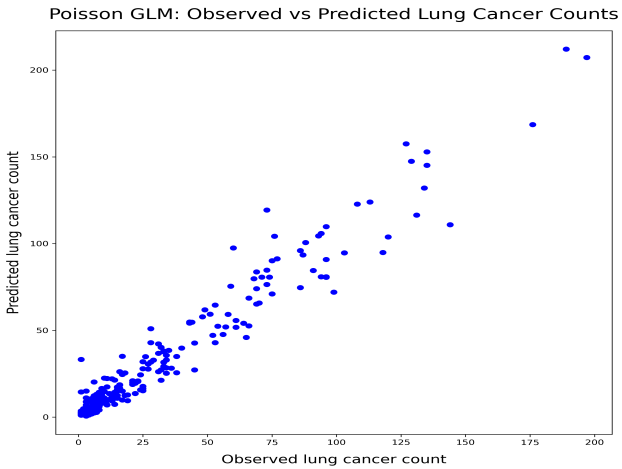


Table 2: Gain-based Feature Importance

Feature	Importance
Median_Household_Income	26.08
ZCTA_pm2_5	6.787
OBESITY_CrudePrev	5.602
Pct_Population_Female_65andOver	4.88
Pct_Hisp_Female_Between18and65	4.859
CSMOKING_CrudePrev	2.414
BINGE_CrudePrev	1.775
Pct_Population_Male_65andOver	1.69
Pct_Hisp_Female_65andOver	1.47
sdi_score	1.31
Pct_White_Male_Between18and65	1.205
Pct_White_65andOver	1.193
Pct_White_Male_65andOver	1.19
Pct_Hisp_65andOver	1.166
Pct_Black_Female_Between18and65	1.122
Pct_White_Female_Between18and65	1.108
Pct_Black_Female_65andOver	1.061
Pct_Hisp_Male_Between18and65	0.992
Pct_BelowPoverty_18andOver	0.399

Model performance on test data

Poisson generalized linear model



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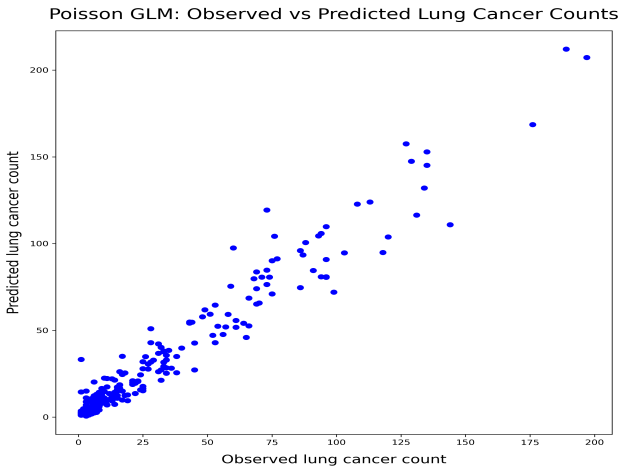
Mean absolute error: 6.313



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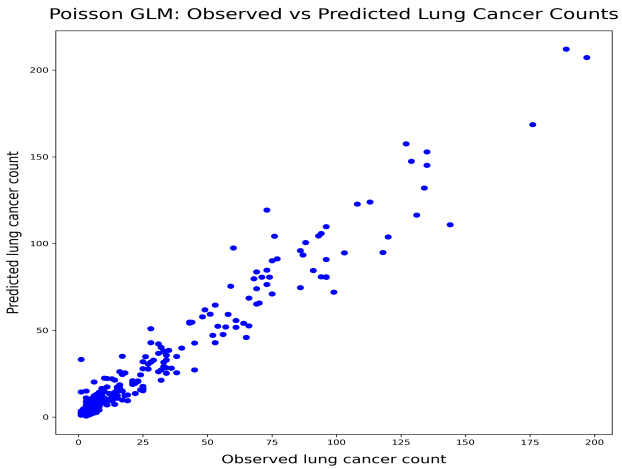

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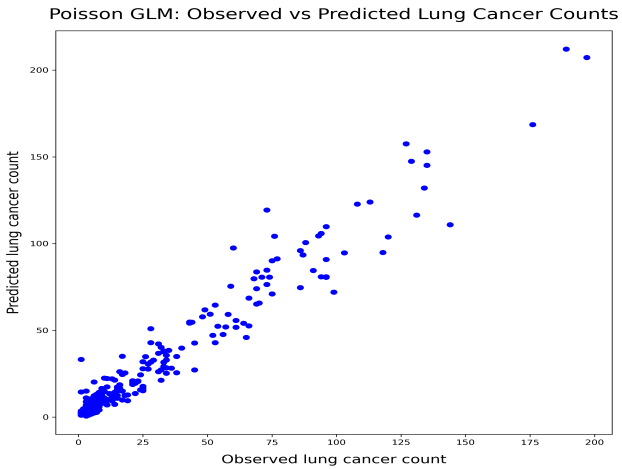

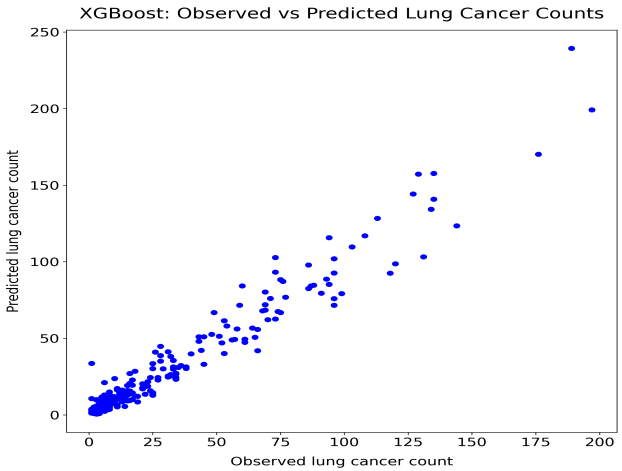

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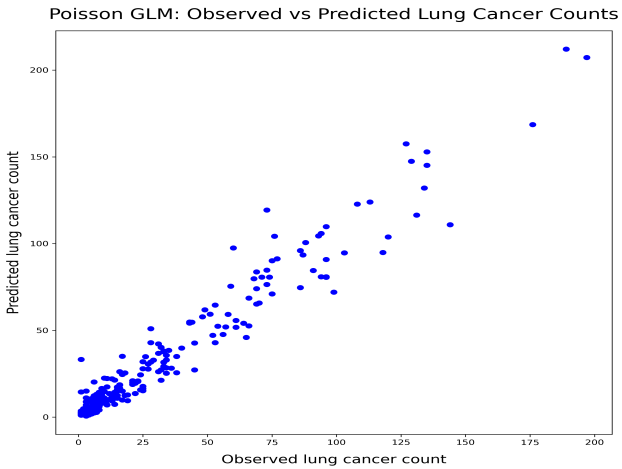
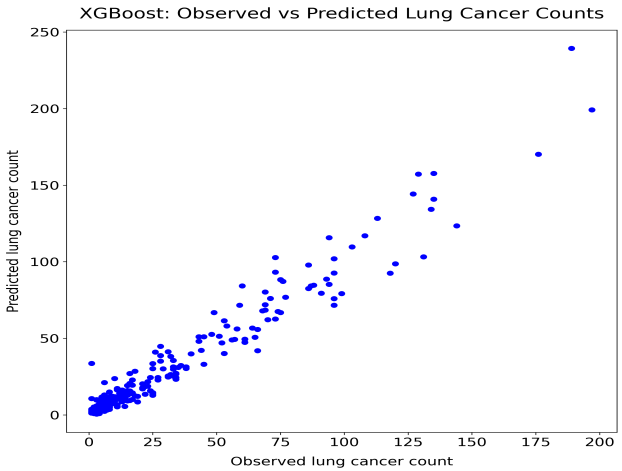


XGBoost

Mean absolute error: 5.963



Conclusion

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Poverty and Hispanic populations show negative associations

Smoking is positively associated while Income and PM2.5 are modestly negatively associated

Median Household Income and PM2.5 are the most important features in predicting lung cancer prevalence

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XGBoost improved prediction accuracy by 5.54% compared to the Poisson Generalized linear model

That concludes our presentation

Thank you for your attention!